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TESTS FOR SPHERICITY UNDER CORRELATED MULTIVARIATE REGRESSION EQUATIONS MODEL\*

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and

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**University of Pittsburgh** 

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## TESTS FOR SPHERICITY UNDER CORRELATED MULTIVARIATE REGRESSION EQUATIONS MODEL\*

Shakuntala Sarkar

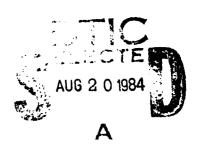
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## Tests for Sphericity Under Correlated Multivariate Regression Equations Model

Shakuntala Sarkar and P. R. Krishnaiah

#### **ABSTRACT**

In this report, the authors considered some tests for sphericity of the error covariance matrix under a correlated multivariate regression equations (CMRE) model. Asymptotic distributions of the test statistics associated with the above procedures are also derived.

Keywords and Phrases: Sphericity, CMRE model, econometrics, multivariate regression.

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#### 1. INTRODUCTION

Extensive research has been done in the past on various problems connected with the classical multivariate regression model since this model plays a very important role in many problems like prediction. The multivariate regression model is nothing but a model with correlated univariate regression equations with a common design matrix. But, there are many situations when it is unrealistic to assume that the design matrices are the same. One such situation is when some of the observations on certain variables are missing. This situation has been dealt with in the statistical literature (e.g., see Srivastava (1966) and Trawinski (1961)) to a limited extent. Another situation is when the design matrices of different regression equations are not the same but none of the observations are missing. For example, the same independent variables may not be good to predict each and every dependent variable.

In the sequel, we will refer to the model based upon correlated univariate regression equations as the correlated regression equations (CRE) model. In econometric literature, the CRE model is known as seemingly unrelated regression equations model. Motivated by applications in economics, Revankar (1974, 1976), Srivastava (1970, 1973), Zellner (1962, 1963) and some other econometricians considered the problem of estimation of parameters under the CRE model when the underlying distribution is multivariate normal. Recently, Sarkar and Krishnaiah (1984) considered the problem of estimation of parameters under the CRE model when the underlying distribution is elliptically symmetric. Approximations to the distributions of the regression vector under the CRE model were discussed in Maekawa (1982) and Kariya and Maekawa (1982).

Kariya, Fujikoshi and Krishnaiah (1983) considered a model based upon two correlated multivariate regression equations and they refer to it as the correlated multivariate regression equations (CMRE) model. Under the above model, Kariya, Fujikoshi and Krishnaiah discussed various procedures for testing for the independence of the two sets of variables and also derived the asymptotic distributions of the statistics associated with the above test procedures. But, no work was done so far on tests for sphericity under the CMRE model.

In this paper, we discuss asymptotic distributions of various test statistics for sphericity under a CMRE model. The likelihood ratio test for sphericity was derived by Mauchly (1940) when the underlying distribution is a multivariate normal with unknown mean vector. Lee, Krishnaiah and Chang (1977) approximated certain powers of the likelihood ratio test statistic for sphericity with Pearson's type I distribution and the accuracy of this approximation is good for all practical purposes. If we know in advance about the structure of the covariance matrix, we can take advantage of this knowledge to propose more efficient estimates of the location parameters and better tests on these location parameters. So, it is quite important to investigate the structure of the covariance matrix of the underlying distribution and the independence of the two regression equations. The results derived in this paper are useful in studying the robustness of the LRT test for sphericity when the assumption of the same design matrix is violated under the usual multivariate regression model.

In Section 2, we give some preliminaries and state the problems that will be investigated in this paper. Throughout this paper, we use estimate of the covariance matrix which is based upon the residuals connected with the regression equations. In Section 3, an asymptotic expression is obtained for the null distribution of the LRT-like test statistics for sphericity. When the design matrices of the regression equations are the same, the above test statistic reduces to the LRT test. For large samples, the asymptotic distribution of the LRT-like test is chi-square and it is the same as the asymptotic distribution of the LRT test statistic for sphericity when the design matrices of the regression equations are the same. But, if we take higher order terms, the expressions for the distributions will be different. In Section 4, we derive the asymptotic nonnull distribution of the LRT-like test for sphericity under the CMRE model under fixed alternatives. The expression obtained involves normal density and Hermite polynomials. The asymptotic distribution of the LRT-like test under local alternatives is given in Section 5. The expression derived in this section involves a linear combination of noncentral chi-square variables. The results of Section 3-5 are derived under the assumption that the underlying distribution is multivariate normal. In Section 6, we have shown that the results of earlier sections remain true when the joint distribution of all the observations is elliptically contoured. Section 7 is devoted to a derivation of the moments of the estimate of the covariance matrix when the joint distribution of the observations on each variable is elliptically contoured but we do not assume that the joint distribution of all observations is elliptically contoured. In Section 8, it is shown that the asymptotic null distribution of the LRT-like test statistic is a linear combination of chi-square variables with one degree of freedom when the underlying distribution is as assumed in Section 7.

#### 2. PRELIMINARIES

Consider two correlated regression equations

$$Y_1 = X_1\theta_{11} + E_1$$
  
 $Y_2 = X_2\theta_{22} + E_2$  (2.1)

where the design matrices  $X_1$ :  $n \times r_1$ ,  $X_2$ :  $n \times r_2$  are known and are assumed to be of full column rank. The matrices  $\theta_{11}$ :  $r_1 \times p_1$  and  $\theta_{22}$ :  $r_2 \times p_2$  of the parameters are unknown. We assume that the rows of  $E = (E_1, E_2)$  are distributed independently as multivariate normal with mean vector 0 and covariance matrix  $\Sigma$ , where

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \tag{2.2}$$

and  $\Sigma_{ij}$  is of order  $p_i \times p_j$ . An estimate of  $\Sigma$  is  $\frac{1}{n}S$  where

$$s = \hat{E}^{\dagger} \hat{E} = \begin{pmatrix} Y_1^{\dagger} Q_1 Y_1 & Y_1^{\dagger} Q_1 Q_2 Y_2 \\ Y_2^{\dagger} Q_2 Q_1 Y_1 & Y_2^{\dagger} Q_2 Y_2 \end{pmatrix}$$
 (2.3)

and

$$Q_{i} = I_{n} - X_{i}(X_{i}^{*}X_{i})^{-1}X_{i}^{*}. \qquad (2.4)$$

In this paper, we are interested in investigating the asymptotic null and nonnull distributions of various test statistics associated with testing the hypothesis  $H_0$ :  $\Sigma = \sigma^2 I$  where  $\sigma^2$  is an unknown constant.

We now discuss a representation of S which is used repeatedly in the sequel in deriving some of the distributions. This representation is due to Kariya, Fujikoshi and Krishnaiah (1983) and it is given in Lemma 2.1. Consider the transformation

$$W_{i} = Z_{i}^{\dagger}Y_{i} = \begin{pmatrix} M_{i} \\ U_{i} \end{pmatrix}$$
 (2.5)

where  $M_i$  is of order  $(r_0-r_i) \times p_i$  and  $U_i$  is of order  $(n-r_0) \times p_i$ . Also  $Z_i$ :  $(n-r_i) \times n$  satisfies  $Z_i'Z_i = I_{i-r_i} \cdot Z_iZ_i' = Q_i$  and is chosen in the following special way.

Let  $Z_0$ :  $n \times (n-r_0)$  be a matrix satisfying

$$Q_0 = Z_0 Z_0^{\dagger}, \ Z_0^{\dagger} Z_0 = I_{n_0}, \ n_0 = n - r_0$$
 (2.6)

where  $Q_0 = I - X(X^*X)^+ X^*$ , and  $X = [X_1, X_2]$  where  $A^+$  denotes the Penrose inverse of A. Further, let  $\overline{Q}_j$  be the projection matrices onto  $L(X) \cap L(Q_j)$ , (j = 1, 2) where  $L(\Lambda)$  denotes the column space of the matrix A. Also, let  $\overline{Z}_j$  be a matrix satisfying

$$\bar{Q}_{j} = \bar{Z}_{j} \bar{Z}_{j}^{i}$$
 and  $\bar{Z}_{j}^{i} \bar{Z}_{j}^{i} = I_{0}^{-r}$ . (2.7)

Then choose

$$z_1 = (\bar{z}_1, z_0), z_2 = (\bar{z}_2, z_0).$$
 (2.8)

It is easy to verify that

$$Z_{i}^{\dagger}Z_{i} = I_{n_{i}}$$
 for  $n_{i} = n - r_{i}$  and  $Z_{i}Z_{i}^{\dagger} = Q_{i}$ ,

where  $Q_i$  is given in (2.4). Note that under  $H_0$ , the rows of  $W_i$  are independently and identically distributed (i.i.d.) as multivariate normal with mean vector 0 and dispersion matrix  $\sigma^2 I_{p_i}$ . Also,  $W_1$  and  $W_2$  are distributed independent of each other.

From (2.3) and (2.4) we obtain

$$S = \begin{pmatrix} W_1^t W_1 & W_1^t Z_1^t Z_2 W_2 \\ W_2^t Z_2^t Z_1 W_1 & W_2^t W_2 \end{pmatrix} = G + B, \qquad (2.9)$$

where

$$G = \begin{pmatrix} U_1^{\dagger} \\ U_2^{\dagger} \end{pmatrix} (U_1 \quad U_2) \tag{2.10}$$

$$B = \begin{pmatrix} M_1^{\prime}M_1 & M_1^{\prime}KM_2 \\ M_2^{\prime}K^{\prime}M_1 & M_2^{\prime}M_2 \end{pmatrix}, K = \overline{Z}_1^{\prime}\overline{Z}_2.$$
 (2.11)

These results can be summarized in the following lemma:

Lemma 2.1. The matrix S defined by (2.3) can be written as G+B, where G and B are defined by (2.10) and (2.11) respectively. Under  $H_0$ , G is distributed as  $W_p(n_0, \sigma^2 I_p)$ , where  $p = p_1 + p_2$  and  $n_0 = n - r_0$  and  $row(M_1)$  is distributed as  $N_{(r_0 - r_1)} p_1 = 0$ ,  $N_{(r_0$ 

3. ASYMPTOTIC NULL DISTRIBUTION OF THE LRT-LIKE TEST STATISTIC The hypothesis  $H_{\hat{O}}$  can be tested by using the statistic

$$\Lambda = \frac{|s|^{n/2}}{(trS/p)^{np/2}}.$$
 (3.1)

When  $X_1 = X_2$ , the above statistic is the likelihood ratio test statistic for sphericity. We will derive the null distribution of T = a.T where

$$T = -2 \log \Lambda$$

$$= n[p \log tr S - \log |S| - p \log p]$$
(3.2)

and  $a = (n_0/n) \le 1$ , under the assumption that  $K = \overline{Z}_1'\overline{Z}_2 = O(1)$  as  $n_0 \to \infty$ . Here we note that  $\Lambda$  is not the LRT test statistic when  $X_1 + X_2$ .

Let

$$V = \sqrt{n_0} \left( \frac{G}{n_0} - \sigma^2 I_p \right)$$
 (3.3)

so that

$$G = n_0(\sigma^2 I_p + \frac{V}{\sqrt{n_0}})$$
 (3.4)

So

$$S = n_0 \sigma^2 (I+A), \qquad (3.5)$$

where

$$A = (\frac{V}{\sqrt{n_0}}, \frac{2}{\sigma^2}).$$

Now

$$\log |S| = p \log (n_0 \sigma^2) + \log |I+A|$$
 (3.6)

$$\log \operatorname{tr} S = \log (n_0 \sigma^2) + \log p + \log (1 + \frac{\operatorname{tr} A}{p}).$$
 (3.7)

From (3.2), (3.6) and (3.7) we obtain

$$\tilde{T} = T_0 + \frac{1}{\sqrt{n_0}} (T_1 + T_2),$$
 (3.8)

$$T_0 = \frac{1}{2\sigma^4} \left[ \text{tr } V^2 - \frac{(\text{tr } V)^2}{p} \right]$$
 (3.9)

$$T_1 = \frac{1}{3\sigma^6} \left[ \frac{(tr v)^3}{p^2} - tr v^3 \right]$$
 (3.10)

$$T_2 = \frac{1}{4} [tr(VB) - \frac{trVtrB}{p}].$$
 (3.11)

The characteristic function of T is

$$\phi(t) = E[e^{it T}]$$

$$= E[e^{it T_0} \{1 + \frac{it}{\sqrt{n_0}} T_1\}] + E[e^{it T_0} \frac{it}{\sqrt{n_0}} T_2] + O(n_0^{-1})$$

$$= \phi_1(t) + \phi_2(t) + O(n_0^{-1})$$
(3.12)

where

$$\phi_1(t) = E[e^{it T_0} \{1 + \frac{it}{\sqrt{n_0}} T_1\}]$$
 (3.13)

$$\phi_2(t) = E[e^{it T_0} \frac{it}{\sqrt{n_0}} T_2].$$
 (3.14)

Note that the characteristic function of  $-\frac{2n_0}{n}$  log  $[\frac{|G|}{n}]^{n/2}$  is  $\phi_1(t) + O(n_0^{-1})$  where  $G \sim W_p(n_0, \sigma^2 I_p)$ . So we know that

$$\phi_1(t) = (1-2it)^{-f/2} + 0(n_0^{-1})$$
 (3.15)

where f = (p(p+1)/2) - 1.

Next we consider  $\phi_2(t).$  Taking expectations with respect to  $\texttt{M}_1^{\prime}$  s only yields

$$\begin{split} \mathbf{E} [\mathbf{tr} \, \mathbf{VB}] &= \, \mathbf{E} [\mathbf{tr} (\mathbf{V}_{11} \mathbf{M}_{1}^{\mathsf{H}} \mathbf{M}_{1}^{\mathsf{+}} \, \mathbf{V}_{12} \mathbf{M}_{2}^{\mathsf{H}} \mathbf{K}^{\mathsf{H}}_{1} + \mathbf{V}_{21} \mathbf{M}_{1}^{\mathsf{H}} \mathbf{K} \mathbf{M}_{2}^{\mathsf{+}} + \mathbf{V}_{22} \mathbf{M}_{2}^{\mathsf{H}} \mathbf{M}_{2}^{\mathsf{+}}) \, ] \\ &= \, \mathbf{tr} [\mathbf{V}_{11} \mathbf{E} (\mathbf{M}_{1}^{\mathsf{H}} \mathbf{M}_{1}^{\mathsf{+}}) + \mathbf{V}_{22} \, \mathbf{E} (\mathbf{M}_{2}^{\mathsf{H}} \mathbf{M}_{2}^{\mathsf{+}}) \, ] \\ &= \, \sigma^{2} (\mathbf{r}_{0}^{\mathsf{-}} \mathbf{r}_{1}) \, \mathbf{tr} \, \, \mathbf{V}_{11}^{\mathsf{+}} + \sigma^{2} (\mathbf{r}_{0}^{\mathsf{-}} \mathbf{r}_{2}^{\mathsf{+}}) \, \mathbf{tr} \, \mathbf{V}_{22}^{\mathsf{+}} \end{split} \tag{3.16}$$

$$\begin{split} \mathbf{E}[\mathsf{tr}\,\mathbf{B}] &= \mathbf{E}[\mathsf{tr}\,\,\mathbf{M}_1^{\mathsf{t}}\mathbf{M}_1 + \mathsf{tr}\,\,\mathbf{M}_2^{\mathsf{t}}\mathbf{M}_2] \\ &= \mathsf{tr}[\sigma^2(\mathbf{r}_0 - \mathbf{r}_1)\mathbf{I}_{\mathbf{p}_1} + \sigma^2(\mathbf{r}_0 - \mathbf{r}_2)\mathbf{I}_{\mathbf{p}_2}] \\ &= [\sigma^2(\mathbf{r}_0 - \mathbf{r}_1)\mathbf{p}_1 + \sigma^2(\mathbf{r}_0 - \mathbf{r}_2)\mathbf{p}_2]. \end{split} \tag{3.17}$$

From (3.14)

$$\phi_{2}(t) = E[e^{it T_{0}} \frac{it}{\sqrt{n_{0}}} \frac{(r_{2}-r_{1})}{p \sigma^{2}} \{p_{2} tr V_{11} - p_{1} tr V_{22}\}]$$
 (3.18)

where

$$v = \begin{pmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \end{pmatrix}; v_{ij} : p_i \times p_j.$$

Now, note that the limiting distribution of  $V = (v_{ij})$  in (3.3) is the distribution of  $\overline{V} = (\overline{v}_{ij})$ , where  $\overline{v}_{ii} \sim N(0,2\sigma^4)$ ,  $\overline{v}_{ij} \sim N(0,\sigma^4)$  i  $\neq$  j and  $\overline{v}_{ij}$  (i  $\leq$  j)'s are all independent, and that the density f of V can be expressed as

$$f(V) = f_0(V) + \frac{1}{\sqrt{n_0}} f_1(V) + \frac{1}{n_0} f_2(V) + \dots$$

where  $f_0(V)$  is the p.d.f. of  $\tilde{V}$ . Next, let

$$v^{*'} = (v_1^*, v_2^*, \dots v_2^*),$$

$$v^{*'} = (v_1, v_2, \dots v_p, v_{12}, \dots v_{1p}, v_{21}, \dots v_{2p}, \dots v_{p1}, \dots v_{pp-1}).$$
(3.19)

Then the limiting distribution of  $v^*$  is

$$N_{p^2} (0, D_{\sigma})$$
 (3.20)

where  $D_{\sigma} = Diag(2\sigma^4, \dots, 2\sigma^4; \sigma^4, \dots, \sigma^4)$ .

Further note that

$$T_{0} = \frac{1}{2\sigma^{4}} \left[ \sum_{i \neq j} \sum_{i \neq j} v_{ij}^{2} + \frac{1}{p} \{ (p-1) \sum_{i = j} v_{ii}^{2} - \sum_{i \neq j} v_{ii}^{2} \} \right]$$

$$= \frac{1}{2\sigma^{4}} v_{i}^{*'} A^{*} v_{i}^{*}, \text{ say}$$
(3.21)

where A\* depends on p.

So,

$$\phi_{2}(t) = C \frac{1t}{\sqrt{n_{0}}} \int \exp\{-\frac{1}{2} v^{*'} (D_{0}^{-1} - \frac{it}{\sqrt{4}} \Lambda) v^{*}\} \left[p_{2} \sum_{p_{1}+1}^{p_{1}} v_{1}^{*} - p_{1} \sum_{p_{1}+1}^{p} v_{1}^{*}\right] dv^{*} + O(n_{0}^{-1})$$

$$= 0 + O(n_{0}^{-1})$$
(3.22)

Using (3.12), (3.15) and (3.22), we get

$$\phi(t) = (1-2it)^{-f/2} + 0(n_0^{-1})$$
 (3.23)

where f = (p(p+1)/2) - 1. Now, inverting the right side of (3.23) yields the following expression for the asymptotic distribution of T:

$$\Pr(\tilde{T} \leq x) = \Pr(\chi_{f}^{2} \leq x) + O(n_{0}^{-1}),$$

where f = (p(p+1)/2) - 1

4. ASYMPTOTIC NON-NULL DISTRIBUTION OF THE LRT-LIKE TEST STATISTIC UMDER FIXED ALTERMATIVE

Let us consider the alternative  $H_1$ : not  $H_0$ . Since the test statistic  $\Lambda$  is a function of the eigenvalues of S, we can assume, without loss of generality, that

$$\Sigma = D_{\lambda} = Diag(\lambda_1, \lambda_2, \dots, \lambda_n). \tag{4.1}$$

Also, G, B,  $M_i$ 's,  $n_0$  are defined as in Section 2.2.

Let

$$V = \sqrt{n_0} \left( \frac{G}{n_0} - D_{\lambda} \right).$$
 (4.2)

Under  $H_1$ ,  $G \sim W_p(n_0, D_\lambda)$ . Now

$$S = n_0(D_{\lambda} + \frac{V}{\sqrt{n_0}} + \frac{B}{n_0})$$

$$= n_0 D_{\lambda}(I + A), \qquad (4.3)$$

where

$$A = \left(\frac{1}{\sqrt{n_0}} D_{\lambda}^{-1} V + \frac{1}{n_0} D_{\lambda}^{-1} B\right)$$

$$\log |S| = p \log n_0 + \sum_{i=1}^{p} \log \lambda_i + \log |I + A|$$

$$tr S = n_0 \left(\sum_{i=1}^{p} \lambda_i + tr C\right), \quad C = \left(\frac{V}{\sqrt{n_0}} + \frac{B}{n_0}\right)$$

$$= n_0 p_{\lambda} \left(1 + \frac{tr C}{p_{\lambda}}\right), \quad (4.4)$$

where  $p\overline{\lambda} = \lambda_1^+ \dots + \lambda_p^-$ . Also,

$$p \log tr S = p \log n_0 + p \log p + p \log \overline{\lambda} + p \log (1 + \frac{tr C}{p\overline{\lambda}}). \tag{4.5}$$

Hence

$$T = n \left[ \log \frac{\left(\overline{\lambda}\right)^{p}}{\underset{i=1}{\mathbb{P}} \lambda_{i}} + p \log \left(1 + \frac{\operatorname{tr} C}{p\overline{\lambda}}\right) - \log \left| I + A \right| \right]. \tag{4.6}$$

Now, let

$$\tilde{T} = \sqrt{n_0} \left[ \frac{1}{n} T - \log \frac{\overline{\lambda}^p}{p_{\lambda_1}} \right] 
= \sqrt{n_0} \left[ p \log \left( 1 + \frac{\text{tr C}}{p \overline{\lambda}} \right) - \log |I + A| \right] 
= T_0 + \frac{1}{\sqrt{n_0}} \left( T_1 + T_2 \right) + O(n_0^{-1}),$$
(4.7)

$$T_0 = \sum_{i=1}^{p} \left(\frac{1}{\lambda} - \frac{1}{\lambda_i}\right) v_{ii}$$
 (4.8)

$$T_{1} = -2 \sum_{i}^{p} \sum_{j}^{p} \frac{v_{ij}^{2}}{\lambda_{i}} - \frac{1}{2} \frac{(\sum_{j}^{p} v_{ij})^{2}}{p_{\lambda}^{-2}}$$
 (4.9)

$$T_2 = \sum_{i=1}^{p} (\frac{1}{\lambda} - \frac{1}{\lambda_i}) b_{ii}.$$
 (4.10)

The characteristic function of  $\tilde{\tilde{T}}$  is

$$\psi(t) = \psi_1(t) + \psi_2(t) + O(n_0^{-1}) \tag{4.11}$$

where

$$\psi_1(t) = E[e^{it T_0} (1 + \frac{it}{\sqrt{n_0}} T_1)]$$
 (4.12)

$$\psi_2(t) = E[e^{it T_0} \frac{it}{\sqrt{n_0}} T_2].$$
 (4.13)

Defining  $V^*$  as in (3.19), we see that the density of  $V^*$  is  $p^2 \tilde{\times} 1$ 

$$N_{p^{2}}(0,\Delta) + 0 \quad (n_{0}^{-1/2}), \text{ where}$$

$$\Delta = \text{Diag}(2\lambda_{1}^{2}, \dots, 2\lambda_{p}^{2}, \lambda_{1}\lambda_{2}, \dots \lambda_{1}\lambda_{p}, \lambda_{2}\lambda_{1}, \dots, \lambda_{p}\lambda_{p-1}). \tag{4.14}$$

Let

$$a_i = (\frac{1}{\lambda} - \frac{1}{\lambda_i}), i = 1(1)p$$
 (4.15)

and

$$a' = (a_1, a_2, \dots, a_p, 0, 0, \dots, 0).$$

$$1 \times p^2$$
(4.16)

From (4.8), we know that  $T_0 = a^*v^*$ . Also from (2.9),  $T_1$  can be written as  $v^*\Omega v^*$ , where elements of  $\Omega$ :  $p^2 \times p^2$  depend on  $\lambda_1, \ldots, \lambda_p$  and p. Then from (4.12),

$$\psi_{1}(t) = E[e^{ita'v*} (1 + \frac{it}{\sqrt{n_{0}}} v^{*'}\Omega v^{*})]$$

$$- \frac{t^{2}}{2} a'\Delta a$$

$$= e^{ita'v*} tr (\Omega \Delta) + \frac{(it)^{3}}{\sqrt{n_{0}}} a'\Delta \Omega \Delta a + \frac{(it)^{3}}{\sqrt{n_{0}}} \frac{4\sum_{j=1}^{p} (a_{j}\lambda_{j})^{3}}{3}] (4.17)$$

We now consider  $\psi_2(t)$  . Taking conditional expectation with respect to  $\mathbf{M_i}$  's only yields

$$E_{M}(T_{2}) = E\left[\sum_{i=1}^{p_{1}} a_{i}b_{ii} + \sum_{i=p_{1}+1}^{p_{1}} a_{i}b_{ii}\right]$$

$$= \sum_{i=1}^{p_{1}} a_{i}(r_{0}-r_{1})\lambda_{i} + \sum_{i=p_{1}+1}^{p_{1}} a_{i}(r_{0}-r_{2})\lambda_{i}$$

$$= (r_{0}-r_{1})\sum_{i=1}^{p_{1}} a_{i}\lambda_{i} + (r_{0}-r_{2})\sum_{i=p_{1}+1}^{p_{1}} a_{i}\lambda_{i}$$

$$= K_{1}(r_{0},r_{1},r_{2},a_{i}'s,\lambda_{i}'s,p_{1},p_{2})$$

$$= K_{1}, \text{ say }. \tag{4.18}$$

Hence

$$\psi_{2}(t) = \frac{it}{\sqrt{n_{0}}} K_{1} E[e^{it} a' v']$$

$$= \frac{it}{\sqrt{n_{0}}} K_{1} e^{-\frac{t^{2}}{2} a' \Delta a}.$$
(4.19)

Finally, from (4.11), (4.17) and (4.19). we have

$$\psi(t) = e^{-\frac{t^2\tau^2}{2}} \left[1 + \frac{it}{\sqrt{n_0}} g_1 + \frac{(it)^3}{\sqrt{n_0}} g_3\right] + O(n_0^{-1})$$
 (4.20)

$$\tau^{2} = \underline{a}^{\dagger} \Delta \underline{a} = 2 \sum_{i=1}^{p} (1 - \frac{\lambda_{i}}{\overline{\lambda}})^{2}$$

$$g_{1} = K_{1} + tr(\Omega \Delta)$$

$$g_{3} = \underline{a}^{\dagger} \Delta \Omega \Delta \underline{a} + \frac{4}{3} \sum_{j=1}^{p} \underline{a}_{j}^{3} \lambda_{j}^{3}.$$

$$(4.21)$$

Note that under  $H_1$ ,  $\tau^2 \neq 0$ , so that inverting the rightside of (4.20), we have the following theorem for the asymptotic distribution of  $\tilde{T}$ .

Theorem 4.1. The distribution function of  $T^* = \tilde{T}/\tau = \sqrt{n_0} \left(\frac{1}{n}T - \log\frac{\overline{\lambda}^r}{\Pi\lambda_1}\right)/\tau$  under  $H_1$  can be expanded for large n as

$$Pr[T^* < x] = \Phi(x) - \frac{1}{\sqrt{n_0}} [g_1] \Phi^{(1)}(x) / \tau + g_3 \frac{\Phi^{(3)}(x)}{\tau^3}] + O(n_0^{-1})$$

where  $\phi^{(j)}(x)$  is the j<sup>th</sup> derivative of the standard normal distribution function  $\phi(x)$ ; and  $g_1, g_2$  and  $\tau$  are given by (4.21).

### 5. ASYMPTOTIC NON-NULL DISTRIBUTION OF THE LRT-LIKE TEST UNDER LOCAL ALTERNATIVES

We assume the same structure of  $\Sigma$  as in (4.1), but we consider local alternatives

$$H_{ij}: \lambda_{i} = \lambda + \frac{0}{\sqrt{n_{0}}}, i = 1(1)p$$
 (5.1)

where  $\theta_i$ 's are not all equal. Thus, under  $H_{\theta_i}$ ,

$$D_{\lambda} = \lambda I_{p} + \frac{D_{\theta}}{\sqrt{n_{0}}} \qquad (5.2)$$

where  $D_{\theta} = Diag(0_1, 0_2, \dots, 0_p)$ . Under  $H_{\theta}$ ,

$$G \sim W_{p}[n_{0}, (\lambda I_{p} + \frac{D_{\theta}}{\sqrt{n_{0}}})]. \qquad (5.3)$$

Define V as in (4.2), where  $D_{\lambda}$  is given by (5.2). We then have

$$S = n_0^{\lambda(I_p + A)}, \qquad (5.4)$$

where A =  $((V+D_0)/\lambda \sqrt{n_0}) + (B/\lambda n_0)$ . Expanding log |S| and log tr S in the same way as before, we get

$$\tilde{T} = -2a \log \Lambda, \ a = \frac{n_0}{n} \le 1$$

$$= T_0 + \frac{1}{\sqrt{n_0}} (T_1 + T_2), \qquad (5.5)$$

where

$$T_0 = \frac{1}{2\lambda^2} \left[ tr(V + D_0)^2 - \frac{(tr V + \sum_{i=0}^{p} \theta_i)^2}{p} \right]$$
 (5.6)

$$T_{1} = \frac{1}{3\lambda^{3}} \left[ \frac{\left(\operatorname{tr} V + \sum_{i=1}^{p} \theta_{i}\right)^{3}}{\sum_{i=1}^{q} 2} - \operatorname{tr}(V + D_{\theta})^{3} \right]$$
 (5.7)

$$T_{2} = \frac{1}{\lambda^{2}} \left[ \text{tr } B(V+D_{\theta}) - \frac{\text{tr } B(\text{tr } V + \sum_{i=1}^{p} \theta_{i})}{p} \right].$$
 (5.8)

The characteristic function of T, as before, can be written as

$$\phi(t) = \phi_1(t) + \phi_2(t) + O(n_0^{-1}), \qquad (5.9)$$

where  $\phi_1(t)$ ,  $\phi_2(t)$  have the same expressions as in (3.13), (3.14) respectively.

Now,  $\phi_1(t) + O(n_0^{-1})$  is the characteristic function of  $-2 n_0/n \log[\frac{|G|}{(\frac{tr G}{p})^p}]^{n/2}$ , where under  $H_\theta$ ,  $G \sim W_p[n_0, (\lambda I_p + \frac{D_\theta}{\sqrt{n_0}})]$ , and

hence  $\phi_1(t)$  is known as (see Fujikoshi, 1981)

$$\phi_{1}(t) = \psi_{f}(t; \delta^{2}/\lambda^{2}) \left[1 + \frac{1}{\sqrt{n_{0}}} \sum_{j=0}^{2} \lambda^{-3} b_{j} (1-2it)^{-j}\right] + O(n_{0}^{-1})$$
 (5.10)

where  $\psi_f(t;\Delta)$  is the characteristic function of a noncentral  $\chi^2$  variable with f d.f. and noncentrality parameter  $\delta^2/\lambda^2$ , and

$$f = \frac{(p+2)(p-1)}{2},$$

$$\delta^{2} = \frac{1}{4}[\operatorname{tr} D_{\theta}^{2} - p^{-1}(\operatorname{tr} D_{\theta})^{2}]$$

$$b_{0} = \frac{1}{6}[2\operatorname{tr} D_{\theta}^{3} - 3p^{-1}(\operatorname{tr} D_{\theta})\operatorname{tr} D_{\theta}^{2} + p^{-2}(\operatorname{tr} D_{\theta})^{3}]$$

$$b_{1} = \frac{1}{2} \{-\operatorname{tr} D_{0}^{3} + 2p^{-1} (\operatorname{tr} D_{0}) \operatorname{tr} D_{0}^{2} - p^{-2} (\operatorname{tr} D_{0})^{3} \}$$

$$b_{2} = \frac{1}{6} \{\operatorname{tr} D_{0}^{3} - 3p^{-1} (\operatorname{tr} D_{0}) \operatorname{tr} D_{0}^{2} + 2p^{-2} (\operatorname{tr} D_{0})^{3} \}.$$

Next consider  $\phi_2(t)$ .

Taking conditional expectations with respect to  $M_1$ 's only we

have

$$E(T_2) = \frac{(r_2 - r_1)}{p\lambda} [p_2 \operatorname{tr} \tilde{V}_{11} - p_1 \operatorname{tr} \tilde{V}_{22}] + O(n_0^{-1/2})$$
 (5.11)

where

$$\tilde{\mathbf{v}} = (\mathbf{v} + \mathbf{D}_{\theta}) = \begin{bmatrix} \tilde{\mathbf{v}}_{11} & \tilde{\mathbf{v}}_{12} \\ \tilde{\mathbf{v}}_{21} & \tilde{\mathbf{v}}_{22} \end{bmatrix}$$

 $\tilde{V}_{ij}$ :  $p_i \times p_j$ . Writing  $\tilde{V} = (v_{ij})$ , see that

$$v_{ii} = v_{ii} + \theta_{i}, i = 1, 2, ..., p$$
 $v_{ij} = v_{ij}, i \neq j.$ 

As before, we write  $T_0 = \frac{1}{2\lambda^2} \tilde{v}^* A_0 \tilde{v}^*$ , where

$$\tilde{v}^{*'} = (\tilde{v}_{1}^{*}, \tilde{v}_{2}^{*}, \dots, \tilde{v}_{2}^{*}) 
1 \times p^{2}$$

$$= (\tilde{v}_{11}, \dots, \tilde{v}_{pp}, v_{12}, \dots, v_{1p}, \dots, v_{p1}, \dots, v_{p p-1}), (5.12)$$

and  $\boldsymbol{A}_{0}$  is a function of  $\boldsymbol{\lambda},$  and p. Further note that,

$$E(v^*) = \mu_0 \tag{5.13}$$

$$Var(v^*) = \Delta, \qquad (5.14)$$

and  $\Delta$  is given by (4.14) and (5.1).

Since 
$$\lambda_i = \lambda + 0(\frac{1}{\sqrt{n_0}})$$
,
$$\Delta \xrightarrow[n_0 \to \infty]{} D_0 = \text{Diag}(2\lambda^2, \dots, 2\lambda^2; \lambda^2, \dots, \lambda^2). \tag{5.16}$$

The limiting distribution of  $\tilde{V}$  is that of  $Z=(z_{ij})$  where  $Z_{ii}\sim N(\theta_i,2\lambda^2)$ ,  $Z_{ij}\sim N(0,\lambda^2)$ ,  $i\neq j$  and  $Z_{ij}(i\leq j)$ 's are all independently distributed. Hence, for large n

$$v^* \sim N_{p^2}(\mu_\theta, D_0),$$
 (5.17)

where  $\boldsymbol{\mu}_{\boldsymbol{\theta}}$  and  $\boldsymbol{D}_{\boldsymbol{0}}$  are given by (5.15) and (5.16) respectively.

Hence

$$\phi_{2}(t) = \frac{1}{(\sqrt{2\pi})^{p^{2}} |D_{0}|^{1/2}} \frac{(r_{2}^{-r_{1}})}{p\lambda} \frac{it}{\sqrt{n_{0}}} \int_{e}^{it/2\lambda^{2}\tilde{y}^{*}'} A_{0}\tilde{y}^{*} - \frac{1}{2}(\tilde{y}^{*} - \mu_{0})' D_{0}^{-1}(\tilde{y}^{*} - \mu_{0})}{c'\tilde{y}^{*}} d\tilde{y}^{*}$$

where

$$\frac{\varepsilon'}{1 \times p^2} = \left(p_2 \frac{\varepsilon'}{p_1}, -p_1 \frac{\varepsilon'}{p_2}, 0 \frac{\varepsilon'}{p_2}\right)$$
(5.18)

$$= \frac{(r_2 - r_1)}{p\lambda} \frac{it}{\sqrt{n_0}} \left| 1 - \frac{it}{\lambda^2} D_0 A_0 \right|^{-1/2} \exp\left[ -\frac{1}{2} (u_0' D_0^{-1} u_0 - v_0' \Omega^{-1} v_0) \right] c' v_0}{(5.19)}$$

$$\Omega = (D_0^{-1} - \frac{it}{\lambda^2} A_0)^{-1}$$
 (5.20)

$$\mathbf{v}_{\theta} = \Omega \mathbf{D}_{0}^{-1} \mathbf{\mu}_{\theta}$$

$$= \sum_{r=0}^{\infty} \frac{(\mathbf{i} \mathbf{t})^{r}}{\lambda^{2r}} (\mathbf{D}_{0} \mathbf{A}_{0})^{r} \mathbf{\mu}_{\theta}$$
(5.21)

and c is given by (5.18). Note that

$$(\underline{u}_{0}^{*} \underline{n}_{0}^{-1} \underline{u}_{0} - \underline{v}_{0}^{*} \underline{u}^{-1} \underline{v}_{0})$$

$$= \underline{u}_{0}^{*} [\sum_{r=1}^{\infty} \frac{(it)^{r}}{\lambda^{2r}} (\Lambda_{0} \underline{n}_{0})^{r}] \underline{n}_{0}^{-1} \underline{u}_{0}.$$
(5.22)

Using (5.21) and (5.22) in (5.19) we have

$$\phi_{2}(t) = \frac{(r_{2} - r_{1})}{\mu \lambda \sqrt{n_{0}}} \left[ 1t \left[ 1 - \frac{1t}{\lambda^{2}} \right] D_{0} \Lambda_{0} \right]^{-1/2} \exp\left(-\frac{1}{2} \mu_{0}^{\prime} \left( \sum_{r=1}^{\infty} \frac{(tt)^{r}}{\lambda^{2r}} (A_{0} D_{0})^{r} \right) D_{0}^{-1} \mu_{0} \right)$$

$$= \frac{c^{\prime} \left( \sum_{r=0}^{\infty} \frac{(tt)^{r}}{\lambda^{2r}} \left( D_{0} \Lambda_{0} \right)^{r} \mu_{0} \right).$$

6. THE DISTRIBUTION OF THE LRT-LIKE TEST STATISTIC WHEN THE JOINT DISTRIBUTION OF OBSERVATIONS IS ELLIPTICALLY CONTOURED

We will first discuss briefly elliptically contoured distributions.

If the random vector  $\mathbf{x}$ :  $\mathbf{p} \times 1$  has the characteristic function of the form  $\exp(\mathbf{i} \, \mathbf{t}' \, \mu) + \psi(\mathbf{t}' \, \Sigma \, \mathbf{t})$  where  $\mu$  and  $\mathbf{t}$  are of order  $\mathbf{p} \times 1$ , then  $\mathbf{x}$  is said to be distributed as elliptically contoured distribution and is denoted by  $\mathrm{EC}(\mu, \Sigma; \phi)$ . Various properties of elliptically contoured distributions are discussed in Anderson and Fang (1982), Cambanis, Huang and Simons (1981) and Kelker (1970). Now, let

$$E = (\underbrace{e}_{1}, \dots, \underbrace{e}_{n}) = \begin{pmatrix} e'_{1} \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ e'_{1} \end{pmatrix}$$

where  $e^*$  = (vecE')' =  $(e'_{(1)}, \dots, e'_{(n)})$ . We assume that  $e^*$  =  $E_{np}(0, I_n \otimes \Sigma^*; \phi)$  and  $\Sigma^*$  is proportional to  $\Sigma$  given by (4.1). Then, it is known (see Cambanis, Huang and Simons(1981) and

Anderson and Fang (1982)) that

$$E = R U A$$
,

where  $\Lambda^*\Lambda = \Sigma^*$ ,  $\Lambda : p \times p$ ,  $U : n \times p$ ,  $Vec. U = u^{(np)}$ , distribution function of R is related to  $\phi$  and R is independent of U; here  $u^{(np)}$  is np-dimensional column vector which has uniform distribution on the unit sphere. In addition, "X  $\stackrel{d}{=}$  Y" denotes that the distribution of X is the same as that of Y. Let us

write  $A = (A_1 \quad A_2)$ ,  $p = p_1 + p_2$ . Then we have  $E_1 \stackrel{d}{=} R U A_1$ ,  $E_2 \stackrel{d}{=} R U A_2$ .

Since

$$S = \begin{pmatrix} E_{1}^{\dagger}Q_{1}E_{1} & E_{1}^{\dagger}Q_{1}Q_{2}E_{2} \\ E_{2}^{\dagger}Q_{2}Q_{1}E_{1} & E_{2}^{\dagger}Q_{2}E_{2} \end{pmatrix}$$
(6.1)

we get

trS = 
$$tr(E_1'Q_1E_1 + E_2'Q_2E_2)$$
  
 $\frac{d}{d} = R^2tr(A_1'U'Q_1UA_1 + A_2'U'Q_2UA_2)$  (6.2)

and

$$|\mathbf{s}| = |\mathbf{E}_{1}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{E}_{1}| |\mathbf{E}_{2}^{\mathsf{q}} \mathbf{Q}_{2} \mathbf{E}_{2} - \mathbf{E}_{2}^{\mathsf{q}} \mathbf{Q}_{2} \mathbf{Q}_{1} \mathbf{E}_{1} (\mathbf{E}_{1}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{E}_{1})^{-1} \mathbf{E}_{1}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{Q}_{2} \mathbf{E}_{2}|$$

$$\stackrel{d}{=} \mathbf{R}^{2p} |\mathbf{A}_{1}^{\mathsf{q}} \mathbf{u}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{u} \mathbf{A}_{1}| |\mathbf{A}_{2}^{\mathsf{q}} \mathbf{u}^{\mathsf{q}} \mathbf{Q}_{2} \mathbf{u} \mathbf{A}_{2} - \mathbf{A}_{2}^{\mathsf{q}} \mathbf{u}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{u} \mathbf{A}_{1} (\mathbf{A}_{1}^{\mathsf{q}} \mathbf{u}^{\mathsf{q}} \mathbf{Q}_{1} \mathbf{u} \mathbf{A}_{1})^{-1} \mathbf{A}_{1}^{\mathsf{q}} \mathbf{u}^{\mathsf{q}} \mathbf{Q}_{2} \mathbf{u} \mathbf{A}_{2}|$$

$$(6.3)$$

Hence

$$\frac{|s|}{(trs)^{p}} = \frac{\frac{|A_{1}^{\prime}u^{\prime}Q_{1}uA_{1}||A_{2}^{\prime}u^{\prime}Q_{2}uA_{2} - A_{2}^{\prime}u^{\prime}Q_{2}Q_{1}uA_{1}(A_{1}^{\prime}u^{\prime}Q_{1}uA_{1})^{-1}A_{1}^{\prime}u^{\prime}Q_{1}Q_{2}uA_{2}|}{[tr(A_{1}^{\prime}u^{\prime}Q_{1}uA_{1} + A_{2}^{\prime}u^{\prime}Q_{2}uA_{2})]^{p}}$$
(6.4)

Substituting this we see that  $\Lambda$  is independent of  $R^2$ . Hence the distribution of  $\Lambda$  will be the same as in the normal case. Thus the asymptotic null and nonnull distribution of  $\Lambda$  under assumption (6.1) is the same as in earlier sections.

7. MOMENTS OF THE ESTIMATE OF THE COVARIANCE MATRIX WHEN OBSERVATIONS ON EACH VARIABLE ARE ELLIPTICALLY CONTOURED

In this section, we assume, instead of (6.1), that the covariance matrix of  $e^{t}$  is  $\Sigma R$  I where  $\Sigma$  is given by (4.1),  $e^{t} = (e_{1}^{t}, \dots, e_{p}^{t})$  and

$$\underbrace{\mathbf{e}}_{\mathbf{j}} \sim \mathrm{EC}_{\mathbf{n}}(0, \lambda_{\mathbf{j}}^{*} \mathbf{I}_{\mathbf{n}}; \boldsymbol{\phi}) 
 \tag{7.1}$$

where  $\lambda_{j}^{*} \propto \lambda_{j}$ , j = 1,...p.

It can be verified easily that

$$E(e_{1}^{\dagger}Ae_{1}) = -2\phi^{\dagger}(0) \lambda_{1}^{*}trA$$
 (7.2)

$$E(e_{i}^{\dagger}\Lambda e_{i}) = 0, i \neq j$$
 (7.3)

$$Var(e_{1}^{!}Ae_{1}) = 8 \phi'(0)^{2} \lambda_{1}^{*2} tr A^{2} + 12(\phi''(0) - \phi'(0)^{2}) \lambda_{1}^{*2} \sum_{i=1}^{n} a_{ii}^{2}$$
 (7.4)

for 
$$A = A' = (a_{11})$$

$$Var(e_{i}^{!}Ae_{j}) = 4 \lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)] a_{ii}^{n} + \phi'(0)^{2} \sum_{i \neq i} a_{ij}^{2}, i \neq j.$$
 (7.5)

Note that  $S = \hat{E}'\hat{E}$ 

$$\begin{bmatrix} e_1'Q_1e_1 & \cdots & e_1'Q_1e_p \\ \vdots & & & & & \\ e_p'Q_1Q_1e_1 & \cdots & e_p'Q_1e_p \\ \vdots & & & & \\ e_p'Q_2Q_1e_1 & \cdots & e_p'Q_2Q_1e_p \\ \vdots & & & & \\ e_p'Q_2Q_1e_1 & \cdots & e_p'Q_2Q_1e_p \\ \vdots & & & & \\ e_p'Q_2Q_1e_1 & \cdots & e_p'Q_2Q_1e_p \\ \vdots & & & & \\ e_p'Q_2Q_1e_1 & \cdots & e_p'Q_2Q_1e_p \\ \vdots & & & & \\ e_p'Q_2Q_1e_1 & \cdots & e_p'Q_2Q_1e_p \\ \end{bmatrix}$$

Hence we have

$$E(s_{ii}) = \begin{cases} -2\phi^{\dagger}(0)\lambda_{i}^{*}n_{1}, & i = 1, 2, ..., p_{1} \\ -2\phi^{\dagger}(0)\lambda_{i}^{*}n_{2}, & i = p_{1}+1, ..., p \end{cases}$$
(7.6).

$$n_1 = n - r_1, n_2 = n - r_2$$
  
 $E(s_{ij}) = 0, i \neq j.$  (7.7)

$$Var(s_{ii}) = \begin{cases} 8\phi'(0)^{2}\lambda_{i}^{*2}n_{1} + 12(\phi''(0)^{2})\lambda_{i}^{*2}\sum_{i=1}^{n}q_{ii}^{(1)2}, \\ i = 1, 2, \dots, p_{1} \\ 8\phi'(0)^{2}\lambda_{i}^{*2}n_{2} + 12(\phi''(0) - \phi'(0))^{2}\lambda_{i}^{*2}\sum_{i=1}^{n}q_{ii}^{(2)2}, \\ i = p_{1}+1, \dots, p \end{cases}$$
(7.8)

where  $Q_1 = (q_{ij}^{(1)}), Q_2 = (q_{ij}^{(2)})$ 

$$Var(s_{ij}) = \begin{cases} 4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(1)2} + \phi'(0)^{2}\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(1)2} \\ i,j=1,2,\ldots,p_{1}; i\neq j \end{cases}$$

$$4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(2)2} + \phi'(0)^{2}\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(2)2}]$$

$$i,j=p_{1}+1,\ldots,p; i\neq j$$

$$4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(3)2} + \phi'(0)\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(3)2}]$$

$$i=1,2,\ldots,p_{1}; j=p_{1}+1,\ldots,p$$

$$or i=p_{1}+1,\ldots,p; j=1,2,\ldots,p_{1}$$

$$(7.9)$$

where  $Q_1^{Q_2} = (q_{ij}^{(3)})$ 

$$Cov(s_{ii}, s_{jj}) = \begin{cases} 4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(1)2} \\ i, j = 1, 2, \dots, p_{1}; i \neq j \\ 4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(2)2} \\ i, j = p_{1} + 1, \dots, p; i \neq j \end{cases}$$

$$(7.10)$$

$$4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(1)} q_{\alpha\alpha}^{(2)} \\ i = 1, 2, \dots, p_{1}, j = p_{1} + 1, \dots, p.$$

For simplicity of notation, let

$$r_1 = r_2 = r \implies n_1 = n_2 = n_0$$
, say

where  $n_0 = n-r$ .

Hence

$$E(\frac{S}{n_0}) = Diag(\lambda_1, \dots, \lambda_p)$$
 (7.11)

where  $\lambda_i = -2\phi'(0)\lambda_i^*$ , i = 1, 2, ..., p.

Let us define

$$Z = \sqrt{n_0} \left( \frac{S}{n_0} - D_{\lambda} \right).$$
 (7.12)

Then

$$E(Z) = 0 (7.13)$$

$$p \times p$$

$$Var(z_{ii}) = \begin{cases} 8\phi'(0)^{2}\lambda_{i}^{*2} + 12(\phi''(0) - \phi'(0)^{2})\lambda_{i}^{*2}\sum_{i}^{n} q_{ii}^{(1)2}/n_{0} \\ i = 1, 2, ..., p_{1} \\ 8\phi''(0)^{2}\lambda_{i}^{*2} + 12(\phi''(0) - \phi'(0)^{2})\lambda_{i}^{*2}\sum_{i}^{n} q_{ii}^{(2)2}/n_{0} \\ i = p_{1}+1, ..., p \end{cases}$$
(7.14)

$$Var(z_{ij}) = \begin{cases} 4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(1)2}/n_{0} + \phi'(0)^{2}\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(1)2}/n_{0}] \\ i,j = 1(1)p_{1}; i \neq j \\ 4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(2)2}/n_{0}^{+}\phi'(0)^{2}\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(1)2}/n_{0}] \\ i,j = p_{1}+1,...,p; i \neq j \\ 4\lambda_{i}^{*}\lambda_{j}^{*}[\phi''(0)\sum_{\alpha}q_{\alpha\alpha}^{(3)2}/n_{0} + \phi'(0)^{2}\sum_{\alpha\neq\beta}q_{\alpha\beta}^{(3)2}/n_{0}] \\ i = 1(1)p_{1}; j = p_{1}+1,...,p \\ or i = p_{1}+1,...,p; j = 1(1)p_{1} \end{cases}$$

$$cov(z_{ii}, z_{jj}) = \begin{cases} 4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(1)2}/n_{0} \\ i, j = 1, 2, \dots, p_{1}; i \neq j \end{cases}$$

$$4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(2)2}/n_{0} \\ i, j = p_{1}+1, \dots, p; i \neq j \end{cases}$$

$$4\lambda_{i}^{*}\lambda_{j}^{*}(\phi''(0) - \phi'(0)^{2}) \sum_{\alpha} q_{\alpha\alpha}^{(1)}q_{\alpha\alpha}^{(2)}/n_{0}$$

$$i = 1(1)p_{1}; j = p_{1}+1, \dots, p.$$

$$(7.16)$$

All other elements of Z are uncorrelated. Now make the following assumptions on the design matrices  $Q_1, Q_2$ .

Each of  $\sum_{\alpha=1}^{n} q_{\alpha\alpha}^{(1)} q_{\alpha\alpha}^{(2)} / n_0$ ,  $\sum_{\alpha=1}^{n} q_{\alpha\alpha}^{(j)2} / n_0$ , j=1,2,3 and  $\sum_{\alpha \neq \beta} q_{\alpha\beta}^{(j)2} / n_0$ , j=1,2,3 are of O(1) and we write for large n

$$\sum_{\alpha} q_{\alpha\alpha}^{(j)2}/n_0 = K_1^{(j)}, \qquad j = 1, 2, 3$$

$$\sum_{\alpha \neq \beta} q_{\alpha\beta}^{(j)2}/n_0 = K_2^{(j)}, \quad j = 1, 2, 3$$
and
$$\sum_{\alpha} q_{\alpha\alpha}^{(1)} q_{\alpha\alpha}^{(2)}/n_0 = K_3.$$
(7.17)

Note that the limiting distribution of Z is the same as that of  $\tilde{Z}=(\bar{z}_{1j})$ , where

$$\bar{z}_{ii} \sim N(0, 2\lambda_i^2 \phi), \qquad (7.18)$$

$$\bar{z}_{ij} \sim N(0, \lambda_i \lambda_j \psi), i \neq j$$
 (7.19)

$$\phi = \begin{cases}
1 + \frac{3}{2}(\phi''(0)/\phi'(0)^{2} - 1)K_{1}^{(1)} \\
i = 1, 2, \dots, p_{1} \\
1 + \frac{3}{2}(\phi''(0)/\phi'(0)^{2} - 1)K_{1}^{(2)} \\
i = p_{1} + 1, \dots, p
\end{cases} (7.20)$$

and

$$\psi = \begin{cases}
[K_2^{(1)} + \frac{\phi''(0)}{\phi'(0)^2} K_1^{(1)}], & i,j = 1(1)p_1 \\
[K_2^{(2)} + \frac{\phi''(0)}{\phi'(0)^2} K_1^{(2)}], & i,j = p_1+1, \dots, p \\
[K_2^{(3)} + \frac{\phi''(0)}{\phi'(0)^2} K_1^{(3)}], & i = 1(1)p, & j = p_1+1, \dots, p \\
j = 1(1)p_1, & i = p_1+1, \dots, p.
\end{cases}$$

Also,

$$Cov(\bar{z}_{ii}, \bar{z}_{jj}) = \lambda_i \lambda_j (\frac{\phi''(0)}{\phi'(0)^2} - 1)C, i \neq j$$
 (7.22)

where

$$C = \begin{cases} K_1^{(1)}, & i,j = 1(1)p_1 \\ K_1^{(2)}, & i,j = p_1+1,...,p \\ K_3, & i = 1(1)p_1; & j = p_1+1,...,p. \end{cases}$$
(7.23)

All other elements of  $\overline{2}$  are uncorrelated.

It is known that, all fourth order cumulants, if they exist, can be expressed as a function of a single parameter, k, which characterizes the kurtosis of the distribution.

For  $\Sigma$  as in (4.1), the only nonzero fourth order cumulants of the

elements of E are

$$\kappa_{4}^{i} = E(e_{2i}^{4}) - 3 \lambda_{i}^{2} \qquad \ell = 1(1) n$$

$$= 3\lambda_{i}^{2} (\frac{\phi''(0)}{\phi'(0)^{2}} - 1), \qquad i = 1(1) p$$

$$\kappa_{22}^{ij} = E(e_{\ell i}^{2} e_{\ell j}^{2}) - E(e_{\ell i}^{2}) E(e_{\ell j}^{2})$$

$$= \lambda_{i} \lambda_{j} (\frac{\phi''(0)}{\phi'(0)} - 1), \qquad \ell = 1(1) n,$$

$$i, j = 1(1) p, i \neq j.$$

All other fourth order cumulants of  $e_{ij}$ 's vanish. Note that  $K_4^i/\lambda_1^2$ , is the kurtosis of the marginal distribution of  $i^{th}$  component, and for convenience define  $K_4^i/\lambda_1^2=3k$ , i=1 (1)p; where k characterizes the kurtosis of the distribution. It is clear from above that  $k=(\frac{\phi''(0)}{\phi'(0)^2}-1)$ , so that

$$K_{22}^{i,j} = \lambda_i \lambda_j k.$$

The parameters in the asymptotic distribution of Z can be expressed as functions of k and  $\lambda_i$ 's only.

8. ASYMPTOTIC NULL DISTRIBUTION OF THE LRT-LIKE TEST STATISTIC WHEN THE OBSERVATIONS ON EACH VARIABLE ARE ELLIPTICALLY CONTOURED

Let  $S_0 = S/n_0$ , then from (7.12), we have

$$S_0 = D_A + Z/\sqrt{n_0}$$
 (8.1)

The LRT-like test statistic for sphericity is  $\Lambda = \left[\frac{|S_0|}{(\text{tr }S_0/p)^p}\right]^{n/2}$ .

We are interested in the asymptotic distribution of T = -2 log  $\Lambda$ . Suppose, under  $H_0$ ,  $\lambda_1 = ... = \lambda_p = \sigma^2$ . Then

$$S_0 = \sigma^2(I+A), A = Z/\sigma_2\sqrt{n_0}$$
  
 $\log |S_0| = p \log \sigma^2 + \log |I+A|$   
 $\log tr S_0 = \log \sigma^2 + \log p + \log (I + \frac{tr A}{p}).$ 

Hence,

$$T = n[p log(1 + \frac{trA}{p}) - log|I+A|],$$

let  $r = \frac{n_0}{n}$  T,  $\frac{n_0}{n} \le 1$ , being the correction factor. Then we have

$$\tilde{T} = \frac{1}{2\sigma^4} \left[ \text{tr } Z^2 - \frac{\left(\text{tr } Z\right)^2}{p} \right] + O(n_0^{-1/2}). \tag{8.2}$$

So the characteristic function of T is

$$\phi(t) = E[e^{it T}]$$

$$= E[e^{it T_0}] + O(n_0^{-1/2}), \qquad (8.3)$$

where

$$T_0 = \frac{1}{2a^4} \left[ \text{tr } z^2 - \frac{\left( \text{tr } z \right)^2}{p} \right].$$
 (8.4)

Let us write this as  $z'A_{0z}$ , where

$$z^{z} = (z_{11}, \dots, z_{pp}, z_{12}, \dots, z_{1p}; z_{21}, \dots, z_{2p}, \dots, z_{p1}, \dots, z_{p(p-1)})$$
 (8.5)

and  $A_0$  is a matrix whose elements depend on p and  $\sigma^2$ . We assume that the errors are distributed as in Section 7. Then, asymptotically,

$$z \sim N_{2}(0, \Omega),$$
 (8.6)  
where  $\Omega = (w_{ij})$ 

 $w_{ij}$ 's are given in Section 7, with the restriction that  $\lambda_i = \sigma^2$  for i = 1(1)p. Hence,

$$\phi(t) = E[e^{it z^{t} A_{0} z}] + O(n_{0}^{-1/2})$$

$$= |I - 2 it A_{0} \Omega|^{-1/2}.$$
(8.7)

Inverting the rightside of (8.7), we get

Theorem 8.1 The limiting null distribution as  $n_0 \to \infty$  of T is that of a linear combination of chi-squares with one degree of freedom and the coefficients depending on the fourth order moments of the observations of the parent population, which are functions of  $\sigma^2$  and k.

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